Recommender System and E-Sales

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Abstract

Customers build strong relationships according to new technology models. Therefore, some software is used to find things that the user wants to view or buy online, and the website recommends these products to the customers, called recommender systems. Today, many recommendation systems have been developed for different fields and on a large scale in most electronic companies. In this paper, we study the effect of the company's revenues via e-sales before and after the use of the recommendation systems.

Keywords: Collaborative filtering, E-commerce, Recommender system, Online Sales, Revenue, Customer, Company, Amazon.

1. Introduction

Electronic commerce (EC) systems have seen significant growth in sales volume in recent years, particularly with the rapid advancement of technology and services offered by the Internet. This competition is represented in growing the number of presented products, offering offers, easing payment, as well as simplifying the process of searching for goods for each user based on his directions (Abdul Hussien, Rahma, & Abdulwahab, 2021; Lee, Choi, Moon, & Kim, 2020).One way to make shopping easier for users is to provide a list that suggests a user's merchandise based on user trends, which is known as a recommender system (RS). In this field, many types of research have emerged that suggest different methods to build a RS that improves the efficiency of commercial websites (Guo, Yin, Li, Ren, & Liu, 2018). RS is a part of information filtering that uses many machines learning and statistical techniques to predicate items to users according to specific methods, it provides different items for every customer, whether through the online or offline store (Aggarwal, 2016). This difference is based on the preferences of the previous history for the user or other similar users (Ricci, Rokach, & Shapira, 2011). The system uses several relevant information for users to recommend items according to the type of approaches of the RS that is used. RS has three methods: collaborative filtering (CF), content-based filtering (CBF), and hybrid filtering (Isinkaye, Folajimi, & Ojokoh, 2015; Mishra, Chaturvedi, Mishra, Srivastava, & Bargah, 2017; Ricci et al., 2011). CF has become one of the most widely used method of presenting personalized services to users. The goal behind collaborative filter comes from the idea that people as a whole often get the best recommendations from other people with similar tastes. It involves techniques for matching people interactions based on similar interests and making recommendations accordingly (Reshak, Dhannoon, & Sultani, 2020).

2. Literature review

In recent years, the RS has become hugely popular due to its importance in many fields: entertainment (Netflix: movies recommendations), social networks (Facebook: friends suggestion, or some ads), e-commerce (Amazon: purchase items recommendation). In this section, we present some previous studies dealing with recommendation systems.

1- (Wen, Ding, Liu, & Wang, 2014) The MF was used in addition to the similarity, where the cosine similarity was used instead of the inner product of MF (COSMF), the datasets (Epinions, Douban, Flixter and Movielens10M) were used. The MF was used for its ability to reduce the problem of sparsity in many datasets

2- (Yu, Wang, Wang, & Gao, 2017) Presented a hybrid approach that incorporates item-information into MF method to handle cold-start problem (specifically, new item) called ACMF (Attribute Coupling based MF). They used Cosine similarity to compute the similarity among items. The results showed that the suggested approach outperforms normal recommendation algorithm.

3- (Hwangbo, Kim, Cha, & Applications, 2018) Offered a method for presenting fashion items to customers by reinforcing the current CF procedure for considering the features of fashion products. They also evaluated the ways to purchase these products offline and online in their approach.

4- (Wu et al., 2018) Suggested recommendation system and used four real datasets for experiments. “Kindle Store (KS), Apps-Android (AA), and Amazon-Instant Video (AIV),” are obtained from data of Amazon item (jmcauley.ucsd.edu/data/amazon), while Yelp from (https://www.yelp.com/).

5- (Zhang, Zhang, Wang, & Chen, 2019) A new approach deep variational MF recommendation is suggested for sparse dataset of big scale. It is used to expect the ratings based on latent factors. For the users and items, the latent features are obtained via a deep-nonlinear form.

6- (Lara-Cabrera, González-Prieto, & Ortega, 2020) Implemented the CF through using the deep learning (DL) with MF. Movielens dataset (100K and 1M) ratings were used in this approach, also the FilmTrust that contain 32675 (1508 users and 2071 items) and MyAnimeList that contain 32675 ratings (69600 users and 600 items) were used.

7- (Lee et al., 2020) introduced a recommendation system based on deep learning (applied the Recurrent Neural Network) and experimented with online food markets

8- (Lara-Cabrera et al., 2020) Suggested solving the problems of recommender system through the use of Linked-Open-Data (LOD) and MF. the suggested system retrieves demographic information from the (LOD) base. The Netflix and Movielens (20M) dataset were used to implement this proposal.

9- (Wang, Zhu, Dai, Xu, & Gao, 2021) Implemented a recommendations model to solve the sparsity problem based on MF, which expected users' rating of the items by learning the totality of the low-rank, then effectively decreasing sparsity and cold start issues utilizing prior information.

10- (Li, Zhang, & Zhang, 2021) Suggested a RS algorithm according to content-based and user CF. Taking advantage of CF, when the number of customers and the evaluation level are large, the customre scoring data matrix becomes relatively dense to decrease the matrix sparse and to allow a more accurate CF.

3. Types of Recommender systems

Recommender systems techniques are classified into three types (Nadia F Al-Bakri & Hashim, 2018; Nadia Fadhil AL-Bakri & Hashim, 2019; Isinkaye et al., 2015; Reshak et al., 2020),as shown in Figure (1):

- Content-based filtering (CBF),
- Collaborative filtering (CF),
- Hybrid filtering.

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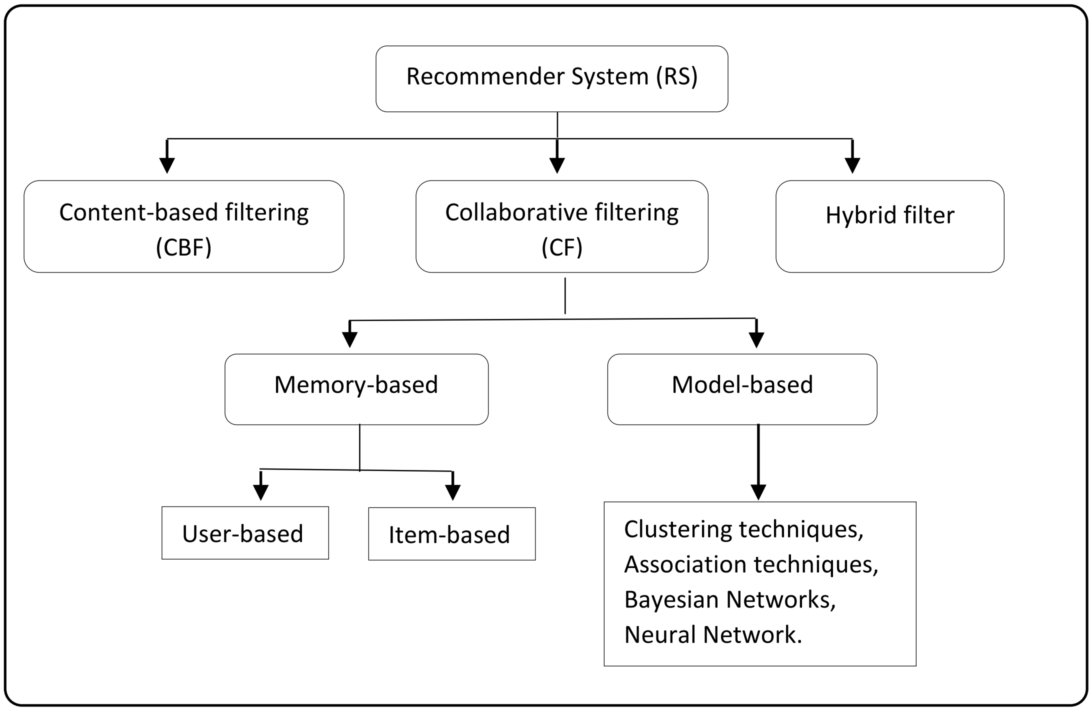

Figure 1: Types of Recommender Systems (Isinkaye et al., 2015).

3.1. Collaborative filter (CF)

The huge amount of data requires mechanisms to filter information efficiently. CF is one of the technique that is used to handle this problem (Mustafa, Ibrahim, Ahmed, & Abdullah, 2017). It involves techniques for matching people based on similar interests and making recommendations accordingly (Raghuwanshi & Pateriya, 2019). There are two methods in CF, which are model-based CF and memory-based CF (Amin, Philips, & Tabrizi, 2019), as shown above in figure (1).

3.1.1. Memory based CF:

In this type, the ratings of user-item sets are predicted based on their neighborhoods, and it classified into user-based CF and item-based CF (Aggarwal, 2016; Reshak et al., 2020). To calculating the similarity between users or items, the Pearson and cosine similarity are utilized, as shown in equations (1 and 2) (Raghuwanshi & Pateriya, 2019).

$$\text{Pearson}= \frac{\sum_{i=1}^{k}(p_{u,i}-\widehat{p_u})\times(p_{v,i}-\widehat{p_v})}{\sqrt{\sum_{i=1}^{k}(p_{u,\text{i}}-\widehat{p_u})^2\times(p_{v,i}-\widehat{p_v})^2}} \qquad \ldots(1)$$

$$\text{Cosine}= \frac{\sum_{i=1}^{k} p_{u,\text{i}}\cdot p_{v,i}}{\sqrt{\sum_{i=1}^{k}(p_{u,i})^2\times(p_{v,i})^2}} \qquad \ldots(2)$$

Where $p_{u,m}$ is the rate for user u to item i while $\widehat{p_u}$ $\hat{p}$, are users u, v mean rating, and k is the total number of items.

4. Recommendation system and Companies Sales

Amazon is one of the leading companies in the field of electronic sales, as well as one of the first companies to use the recommendation system(Smith & Linden, 2017). Amazon uses recommendation systems to a large extent, whether through its websites or even through the use of e-mail, and its sales have increased to 60% (Zhao, Zhang, Friedman, & Tan, 2015), see figure (2). Netflix, a company specialized in showing movies and series over the Internet, held a competition worth one million dollars in order to develop its algorithm by 10% based on the recommendation system. The competition began in 2006 and ended in 2009 with the winning of one of the competing teams with the prize money (Amatriain & Basilico, 2015; Bell, Koren, & Volinsky, 2010), see figure (3) to show the company revenues. Also, YouTube has used recommendation systems in order to display appropriate views to the user (Zhou, Khemmarat, & Gao, 2010). The famous electronic sales site (Alibaba) uses the recommendations systems on its site to ensure that the right product is suggested to the customer (Chen, Zhao, Li, Huang, & Ou, 2019).

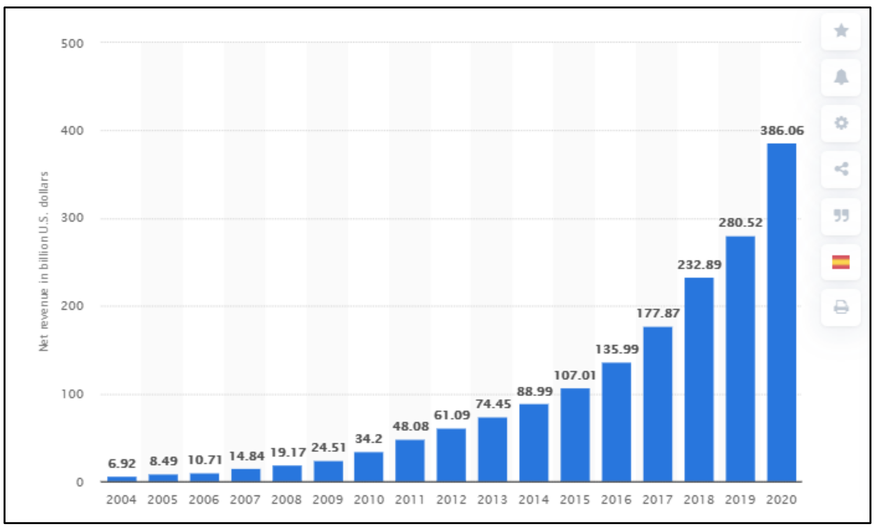

Figure 2: Amazon revenues 2004-2020 (https://www.statista.com/, 2022).

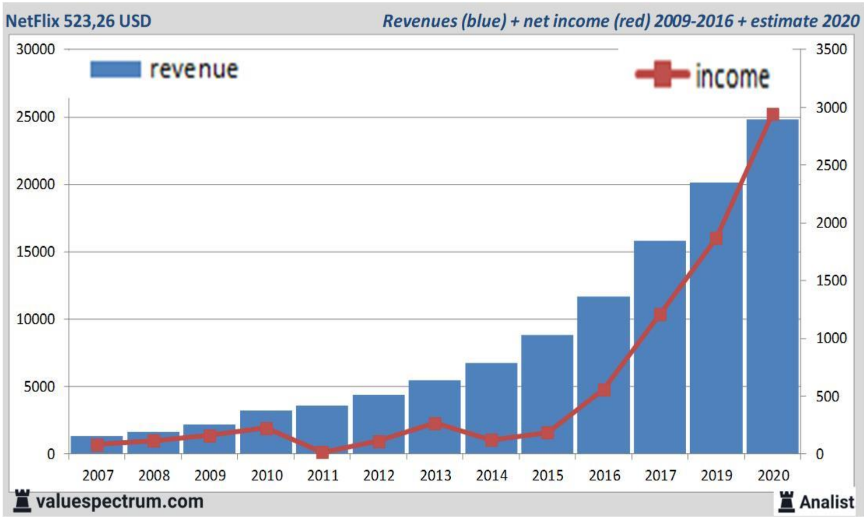

Figure 3: Netflix revenues 2007-2020 (https://www.valuespectrum.com/, 2020).

5. Conclusion and Future Work

Good sales come from good product marketing and this is what the recommendation system does by using complex algorithms to analyze user behavior and then directing sales offers and promotional activities to specific users. By reviewing research, we find that most websites or applications used recommendation systems, and we also find that most, if not all, companies have increased their sales after using this system, and an example of this is the Amazon company that has increased its sales by a large percentage that reached 60%, as well as the million-dollar prize from Netflix to develop its system of recommendations is evidence of the importance of this system and its great impact in attracting viewers to its movies. As a future work, we suggested a detailed analytical study of one of the data of the mentioned companies, then design a program that simulates the company's recommendation and uses other criteria in order to increase the accuracy of these systems.

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